Characterizing Motor Learning of a Novel Reaching Task in a Virtual Environment Using Kinematic Evaluation

by

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ABSTRACT

Virtual environments are used for many physical rehabilitation and therapy purposes with varying degrees of success. An important feature for a therapy environment is the real-time monitoring of a participants' movement performance. Such monitoring can be used to evaluate the environment in addition to the participant's learning.

Methods for monitoring and evaluation include tracking kinematic performance as well as monitoring muscle and brain activities through EMG and EEG technology. This study aims to observe trends in individual participants' motor learning based on changes in kinematic parameters and use those parameters to characterize different types of learners. This information can then guide EEG/EMG data analysis in the future.

The evaluation of motor learning using kinematic parameters of performance typically compares averages of pre- and post-data to identify patterns of changes of various parameters. A key issue with using pre- and post-data is that individual participants perform differently and have different time-courses of learning. Furthermore, different parameters can evolve at independent rates. Finally, there is great variability in the movements at early stages of learning a task. To address these issues, a combined approach is proposed using robust regression, piece-wise regression and correlation to categorize different participant's motor learning.

Using the mixed reality rehabilitation system developed at Arizona State University, it was possible to engage participants in motor learning, as revealed

by improvements in kinematic parameters. A combination of robust regression, piecewise regression and correlation were used to reveal trends and characterize participants based on motor learning of three kinematic parameters: trajectory error, supination error and the number of phases in the velocity profile.

ACKNOWLEDGMENTS

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Chapter 1

INTRODUCTION

A recent trend in rehabilitation has been the use of interactive motion-capture environments for stroke rehabilitation, often referred to as “virtual rehabilitation”. However, care needs to be taken in designing such virtual environments, particularly for populations with various neurological disorders because the complex environments can be confusing or overwhelming. A key question to address is the evaluating the efficacy of interactive environments for motor learning with healthy participants. From studies of healthy participants we can predict if the application of motor learning principles to stroke rehabilitation can carry over when adding new complexities to the situation with virtual tools.

This study is part of a collaborative project to analyze simultaneous EEG and EMG data in order to evaluate the potential for using combinations of kinematics, EEG and EMG to enhance the motor learning and rehabilitation process. EEG and EMG offer a minimally invasive method for connecting motor learning behavior with motor control and neural correlates, respectively. Meanwhile, motion capture provides means for quantifying motor learning as well as rehabilitation.

The primary goals of this study were to 1. Understand if an interactive motion capture environment is effective for training a novel movement, 2. To evoke significant motor learning processes so that the results could be compared with simultaneous EEG and EMG recordings in future studies and 3. To evaluate and categorize different participants' motor learning with consideration to the varying strategies and time courses different participants may utilize.

A challenge to address these goals is to design a task that is novel for non-impaired participants that can evoke movement strategy formation by the participant that may be comparable to that of stroke survivors. Another challenge is to develop a comprehensive method for analyzing participant movement that takes into account individual participant variability and the time-course of the learning process using highly dimensional motion capture data. Furthermore, the designed task needs to satisfy the requirements for adequate EEG and EMG study design while modifying the existing interactive motion capture system. Finally, since the purpose of this work is to help with real—time monitoring and evaluation of rehabilitation and motor learning, it is important to consider all of the challenges that would be present in such an environment such as limited data collection and high participant variability.

Motor Learning

Theories from motor learning have been used as a guiding principle for many modern stroke rehabilitation methods. Motor learning is often defined as the set of processes by which the performance of a new task improves by way of practice and repetition (Schmidt and Wrisberg, 2008). One key characteristic of the motor learning process is a decrease in errors as a task is repeated. Repetition of a movement leads to decrease in movement variability, if it is a highly specific task (Higgens and Spaeth, 1979). However, this reduction is not necessarily indicative of learning by itself, since the reduction might not be a permanent change. There have been several attempts to characterize the different phases of learning motor skills. Fitts and Posner (1967) proposed a three-stage model for the role of cognitive activity in the motor learning process. They suggest that at first there is a highly cognitive component to motor learning when the person is thinking about how to perform the task; second, that there is an associative stage when the person understands which strategies they are performing that are effective; and, finally, an autonomous stage where the learned movement becomes a fully embedded into their actions. This cognitive approach is also paralled by a similar approach focusing on muscular activity suggested by Verikjen et al (1992), referred to as the "systems three-stage theory" (Shumway-Cook and Wollacott, 2007). Studies on motor learning often focus on the first two stages because the final stage can take numerous repetitions to form. A simple two-stage model of learning proposed by Gentile (1972) suggests that in the first stage, the person understands the general purpose of the task and the second stage is for refinement of the task.

The established theories of motor learning suggest that early in the process, there is high variability in movement and a subsequent decrease in variability and error. There have been attempts to model this learning behavior mathematically. Originally, a power law of practice was proposed (Schmidt and Lee 2005, Fits 1964, Newell and Rosenbloom 1981) which related the rate of improvement to the amount of practice. However, recent work (Heathcote et al 2000) has shown that on an individual participant level, an exponential fit is more robust. Nonetheless, these exponential decreases are typically observed with simple goal-directed tasks (Flament et al) and may be eclipsed by participant-specific trends with complex tasks.

While the aforementioned studies often focus on simple movements that result in stereotyped behavior, it is unclear if the changes in kinematic parameters of movement with practice would be the same for more complex movements. It is possible that for complex tasks, different participants would employ different strategies shaped by their previous experiences. While the eventual outcome for different participants is likely to be the same for all participants (e.g. a decreased error to a stabilized error value), it is possible that the different strategies taken during the early learning phases could significantly affect the types of strategies used. Through analysis of kinematic parameters during the key learning phases in early stages where the changes are the largest, it is possible to characterizing different learning mechanisms. This information is useful first for correlating data with EEG and EMG to come up with an ordering of different participants by their strategy and second because an understanding the kinematic time courses and strategies is useful for real time monitoring of kinematic data in rehabilitation environments. Models that take into account different learning strategies could also be used as an evaluative method for different feedback/practice schedules in interactive motion capture rehabilitation systems.

Study Overview

A block design was employed with four blocks of two types. In the first and third blocks participants performed normal reaches to three target locations while receiving audio and visual feedback to help improve their movement performance. In blocks two and four, the participants were told they would need to perform a different movement to the three target locations and would need to rely on the feedback to perform the movement correctly. Methodological details are described in the following section.

Chapter 2

METHODOLOGY

System Description

Upper arm movement data was captured using a 12-camera Optitrack (NaturalPoint Inc.) infrared motion capture system at 100 frames per second. Reflective rigid body marker sets were placed on the back of the hand, wrist, elbow, upper arm, shoulder and torso to track the real-time position of the entire upper extremity and trunk. Each marker set contained three to four reflective markers, which allows the recording of both position and relative rotation between different marker sets placed on the arm. The position data was streamed from the Optitrack Arena software to custom software (BFMA) that creates a rigid body model of the upper extremity. This model was then streamed to another computer that analyses movement of the rigid body model, generates feedback, and records the motion capture data using custom software (Task Control). The custom software was developed in the Mixed Reality Rehabilitation group of the Arts Media and Engineering department at Arizona State University. A block diagram of the system setup follows with arrowheads denoting the direction if information flow. The EEG/EMG components are not the focus of this thesis but were a significant component of the development of the integrated system.

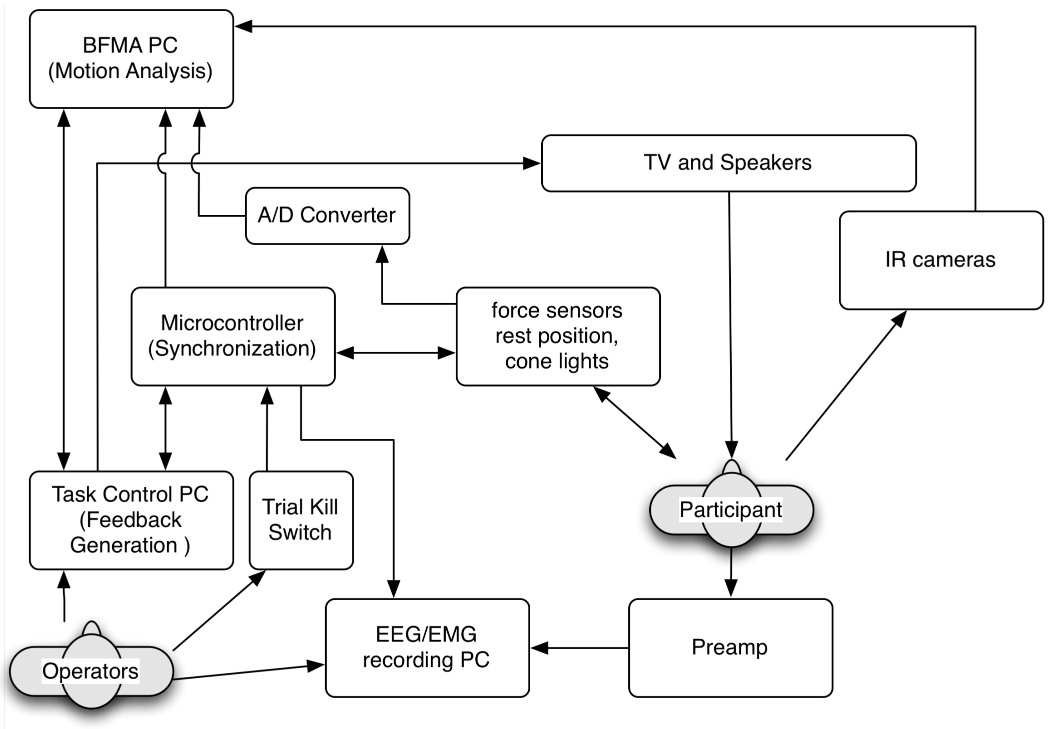

Figure 1. Block diagram of system setup for the current study.

Custom hardware was developed to augment the motion capture monitoring of the participant. First, a rest pad with an embedded switch was built to monitor correct placement of the hand at a consistent rest position as well as to detect when the hand began movement. Three sturdy plastic cones were built using rapid prototyping that contained two force sensors to measure relative grasping forces on the cone. The cone was covered in a cloth cover to hide the force sensors to discourage participants from focusing on the sensors while grasping. In addition, a blue LED light was embedded in the top of the cone to provide an indication to the participant of which cone to grasp next. The cones were attached to a metal track, which allowed repositioning of the cones to a participant's physical anatomy. The cones and the track are presented in *Figure 2*. In addition, the distance of the middle cone from the track was adjustable for further adjustment to each participant's anatomy. A "trial kill" switch was also built to allow the EEG system operator to halt any trial if there is a problem with the EEG or EMG data recording.

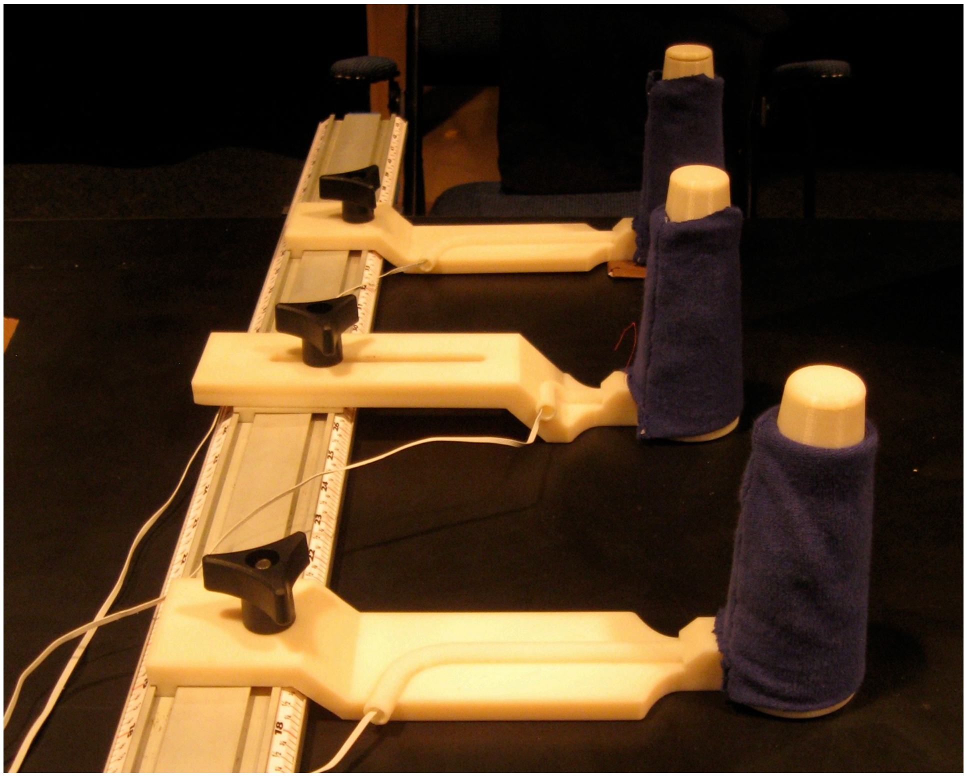

Figure 2. Custom built cone targets with embedded force sensors and LEDS on an adjustable track.

Experiment design

A block design was used for the experiment with four blocks of two types (A and B). In the A blocks, participants were told to make a normal movement to one of three cones. In the B blocks, participants were told that the movement would be modified and they may have to move their hand differently to successfully reach to the cone. Each block consisted of 30 successful reaches. An unsuccessful reach was defined as one where the participant moved prematurely.

For both movements participants were told to return to the same rest position, which was marked with a foam pad. The pad contained a switch that required the participant to rest their hand on the pad in order to continue with the trial. Once the hand was on the rest pad, one of three targets on the table would light up. This would indicate to the participant which cone to reach to. After a few seconds, a green rectangle would show up on the screen that indicated to the participant to begin their reach to the cone that had previously lit up. If the participant moved before the light turned on, the trial would reset. The participants were instructed to remain calm and relaxed between trials. The participant then had 6 seconds to successfully reach and grasp the cone. The participant was seated so that the table height was about 3cm below where the participants elbow bone hangs when the arm was placed in the lap. The three target locations were set based on the participants' physiology. One target was in front of the midline, another was straightforward and one was between the two. They are placed at 85% of the full passive extension of the arm.

For task A, no modifications to the feedback mappings were made so the participants could make natural reaches with minimal error feedback. For task B, the trajectory the participant was supposed to make was modified so that at 33 percent of the distance to the target during the reach, the participant was required to move his hand roughly 10cm further to the right than in a normal reach. Since the original system uses a range of values before feedback becomes responsive, (referred to as a hull) the ranges were reduced at 33 percent and 67 percent of the reach so that the error feedback was more prominent. In previous tests, participants quickly learned modifications to the trajectory error in a few trials. Thus to increase the difficulty of the task, in addition to the trajectory modifications, the expected amount of supination was also modified so that excessive pronation of 40 degrees was required at 33 and 67 percent of the task. These modifications were made to trajectory curves that were generated from other studies of healthy participants using the system. The magnitudes of the parameters were determined beforehand by testing the system with two naïve participants as well as with the three people who had used the system before. The task was designed to require a change in the plan of movement as well as take into account the constraints on the possible movement due to the location of the cones on the table as well as the size of reflective markers worn on the back of the hand.

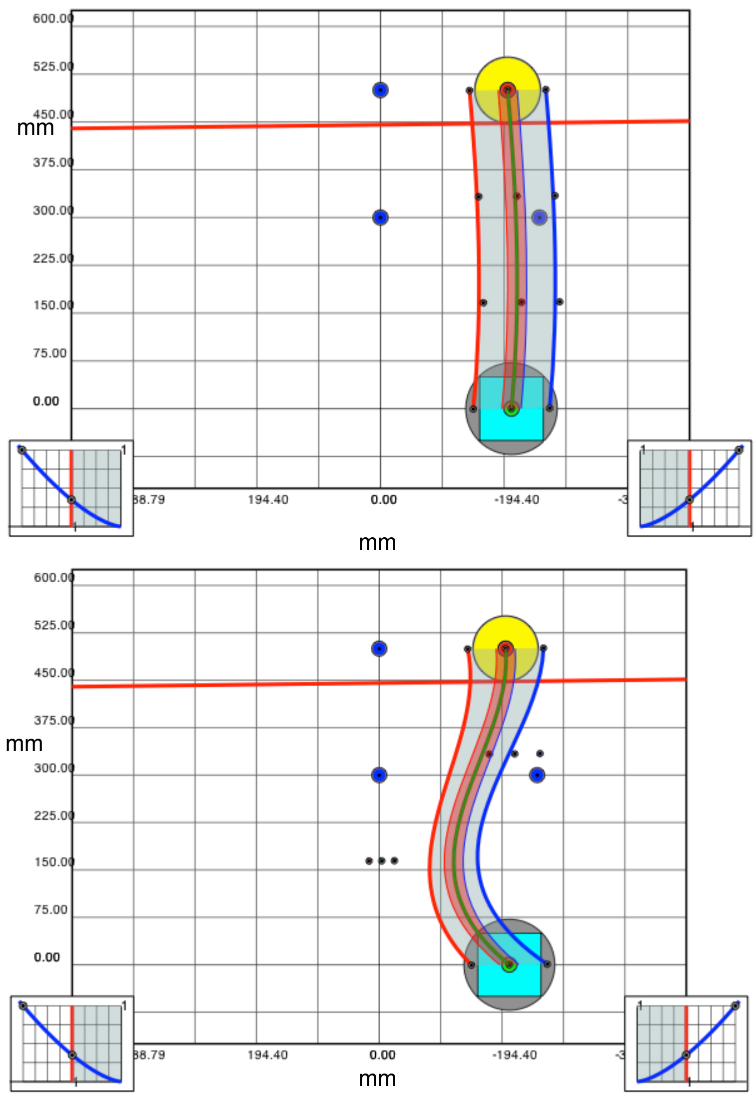

Figure 3. Normal trajectory (top) and altered trajectory (bottom) for a sample target location.

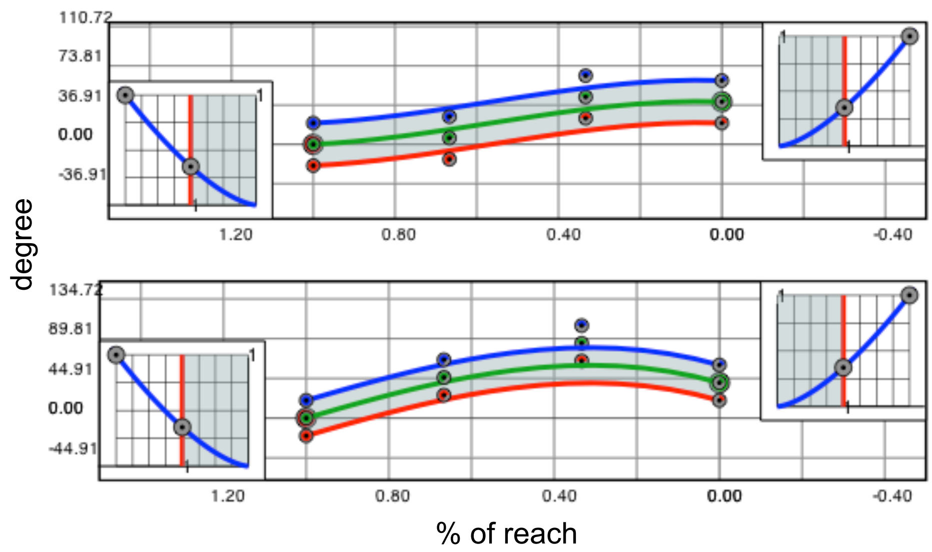

Figure 4. Normal supination curve (top) and modified supination curve (bottom).

Participants

Participants were recruited from a voluntary participant pool who answered that they were right handed and had no history of seizures, neurological disease or damage, that would limit the movement and control of the torso and upper limbs. In addition, participants reported having normal or corrected to normal hearing and vision. Participants were compensated two movie passes for Harkins Movie Theaters for their participation. All recruitment procedures and study protocols were approved by the Institutional Review Board at Arizona State University (protocol #0910004413). The age range of participants was 19-58 with a mean age of 24.09 years. Eleven female participants were recruited and 10 male participants were recruited.

Training

The participants underwent a training period before starting the experimental blocks. In the training period, the participants were allowed to explore the environment as they made reaches towards a cone. In particular, they were asked to try swinging their arm around the space to see how the image on the screen shifted as they moved their hands. Next, they were asked to rotate their wrist (i.e. to pronate and supinate) to see how the image rotates with their hand. Finally, they were asked to move their hand fast or slow to hear the audio mapping related to the speed of the movement. Before progressing to the experimental blocks, it was confirmed with the participant that they understood the different components of the movement and how the components related to the feedback.

Audio and visual feedback

Audio and visual feedback was generated from the participant's movement. These feedback elements were adapted from the Mixed Reality Stroke Rehabilitation system developed at the Arts, Media and Engineering department. A table of the different audio-visual feedback mappings follows.

Table 1

Audio and Visual Feedback Mappings and their Descriptions

Feedback	Audio/visual	Description
Success sound	Audio	Sound of a triangle being struck plays when the correct cone is squeezed and the hand velocity goes to zero.
Real-time trajectory error	Visual	The image stretches in the direction of the error.
Real-time supination error	Visual	The image rotates if the hand is not at the prescribed amount of supination/pronation. If the hand has the correct degree of supination, the image stays upright.
Velocity	Audio	The musical notes playing increase in density as the speed of the hand increases. This can indicate a proper acceleration and deceleration curve (bell shaped velocity curve)
Trajectory error summary	Visual	Red marks appear on the screen after a reach is completed that show a history of trajectory errors that were made during the reach. Marks that are further away from the center indicate errors that were early in the reach and marks close to the center indicate errors that occurred later in the reach.
Detuning	Audio	Sound detunes as errors are made in real time
Go signal	Visual	A green rectangular frame is shown to signal to the user to begin the reach
Cone indicator	Visual	A light glows in the cone that needs to be reach to before the Go Signal is given.

Data Analysis

Pre-processing. Data was first pre-processed to check for errors in data recording and to segment the data into the reaching portion of the movement, which was the focus of subsequent analysis. Data for each reach was inspected visually for any occlusions in the marker data. If there was a simple occlusion (e.g. a sudden jump in a value that returns to the previous values within one frame), the occlusion was removed by using a polynomial spline across the occluded data. If the occlusion resulted in large jumps in values, the data was marked as an outlier and was omitted for kinematic and statistical analysis. Data for participants 8 and 14 were not recorded properly and were omitted from kinematic analyses. Data preprocessing and computation of trajectory and supination errors was performed using MRROfflineTools developed by Yinpeng Chen at the School of Arts, Media and Engineering at Arizona State University. The beginning of the each reach was determined as the onset of movement and the grasp was determined as the location where the force sensors begin to show a reading. The maximum velocity peak, end of the first phase, target hit point and end of a trial are annotated on *Figure 5*.The lower figure shows the force sensor response in blue and red.

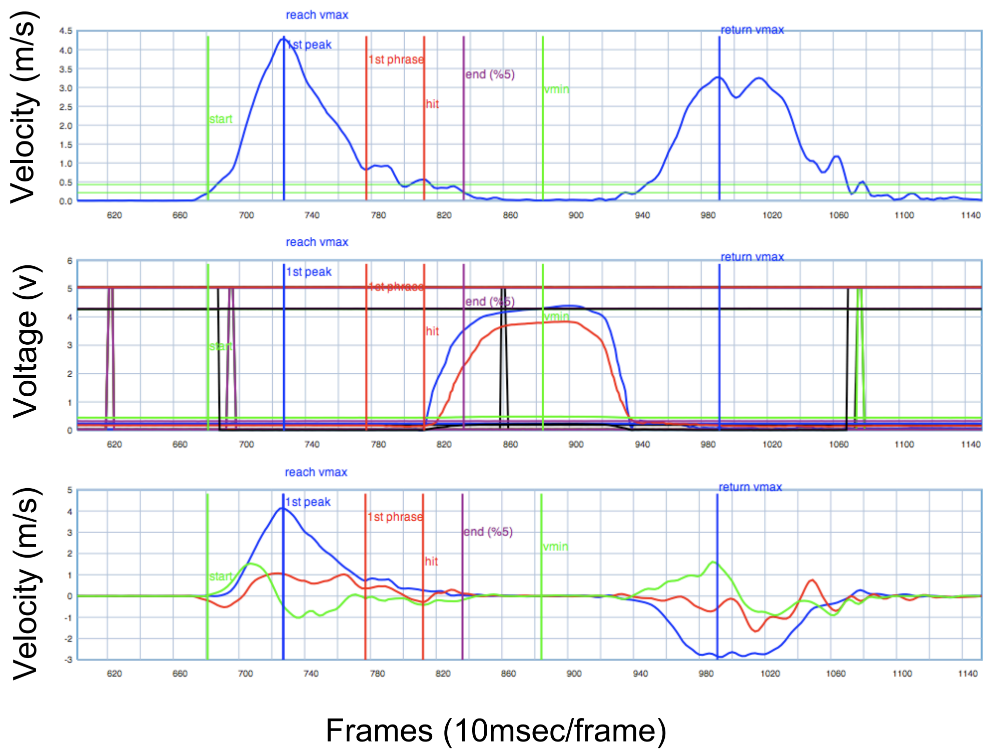

Figure 5. Reach segmentation example for a single reach with velocity profile on top, force sensor readings on the bottom and individual components (x y z) of the velocity. The start of movement, 1st peak/maximum velocity, end of 1st phase, target hit/squeeze and end of the movement are all annotated on the plots.

Kinematic analysis. Three kinematic parameters were calculated from the reaching data for each reach trial and are listed in Table 2. The parameters were all measured from the end-point marker set that was placed on the back of the hand. In addition, the parameters are computer in a local coordinate system orientated from the rest position towards each target location rather than in a global system to allow generalization between target locations. Before computation of the kinematic parameter a 4th order low pass Butterworth filter was applied to the data with a cutoff of 5 hz.

Table 2

Kinematic Parameters Analyzed from Participant Reach Data and their thresholds for inclusion in analysis

Parameter	Description	Outlier threshold
Trajectory Error (TE)	Absolute horizontal maximum error from the prescribed path in table plane	> 30 cm
Supination Error (SE)	Absolute maximum error in supination from the prescribed path divided by the range of motion for the participant	> 2
Number of Phases (NP)	Number of local maximums between start and end of movement	>10

The trajectory error, TE_{reach}, was measured from the position, x(t), of the end-point marker that was placed on the back of the hand. The trajectory error was calculated as the maximum distance the hand was from the prescribed path at the same percentage of reach ($x'_{prescribed}(\%reach(t))$, from the beginning of the movement to the end of the movement (equation 1).

$$TE_{reach} = \max\left|x(t) - x_{prescribed}(\%reach(t))\right|_{t=tstart}^{t=tend} \tag{1}$$

Supination angles, θ(t), were computed using a rotation matrix obtained in a calibration procedure during the experiment. The supination error was then computed as the difference between the supination angle and the prescribed supination at that percent of the reach. In order to normalize the values for different participants ranges of motion, the angles were divided by each participant's range of motion, θ_{ROM}, that was measured during an initial calibration of the system.

$$SE_{reach} = \max\left|\frac{\theta(t) - \theta_{prescribed}(\%reach(t))}{\theta_{ROM}}\right|_{t=tstart}^{t=tend} \tag{2}$$

Velocity, v(t), was computed by taking the derivative of the position of the end-point marker in each direction (x, y, z) and taking the magnitude of the three velocity components. The number of phases in the velocity curve was then computed as the number of local maximums of the velocity curve

$$\mathrm{NP}_{\mathrm{reach}} = \phi(v(t)|_{t=tstart}^{t=tend}) \tag{3}$$

In order to avoid counting small peaks that are not relevant to the overall movement plan, a threshold was established to ensure that the difference between each subsequent reach was at least 5% of the maximum velocity peak value during the reach (equation 4). For all n local maximums only those that satisfied the following equation were counted as local maximums for counting the number of phases:

$$\left[\mathrm{localmax}_{n+1}(v(t)) - \mathrm{localmax}_{n}(v(t))\right] > 0.05 * \max(\mathrm{localmax}(v(t)) \tag{4}$$

The three chosen parameters provide a range of kinematic measures that are related to quality of movement and movement planning. While the Mixed Reality Rehabilitation System can track many other parameters relevant to rehabilitation including amount of compensation or specific joint angles, it was determined that a subset of parameters including the number of phases in the velocity profile, the trajectory error in the horizontal direction and the supination error would be most relevant for healthy participants. In particular the trajectory error and supination error parameters are directly related to the most significant visual feedback components while the velocity measure is an indication of motor planning. Parameters that are more detailed are typically more useful when addressing specific deficits in the movement.

In addition, some thresholds were determined to identify and remove outliers from the analysis. Extremely large values for different parameters are indicative of reach trials where the participant was trying an exaggerated movement to interact with the system, but are not representative of the rest of the reaches during the trial. The thresholds listed in Table 2 were applied to eliminate outliers from analyses.

Modeling

Regression models. Due the great inter-participant variability, group means for different parameters were not meaningful for observing trends for the different kinematic parameters. In addition, taking the average of the block resulted in a loss of the time course of the different kinematic parameters. Since one goal of this project was to correlate kinematic results of motor learning with EEG and EMG data, there was a need to categorize different types of learning.

First, the second block was isolated because that is where the most learning of the task as expected to occur. Visual inspection of the different parameters confirmed that the greatest changes in the different parameters occurred in the second block. While typically curve fitting with exponential or power curves is performed on kinematic data of motor learning, the low number of participants as well as the low number of reaches during a block utilized in this study precluded this type of analysis, as the attempted curve fits had poor R^2 values.

Instead, a robust regression was performed to describe the data either as decreasing, increasing or to have no change for each parameter in block 2 by looking at the slope term from the regression. Robust regression is a modification to standard linear regression that reduces the effect of outliers on the regression curve, making it appropriate for highly variable data. Here a bisquare weighting function was used to down weight outliers when performing the least squares procedure in regression. After performing robust regression, studentized residuals were visually inspected to ensure they were randomly distributed. No obvious trends were observed in the studentized residuals for all the parameters.

One shortcoming of both robust regression and standard regression for motor learning is that for participants with rapid changes in the errors, changes that occurred in a few number of trials could be missed by linear regression, since linear regression assumes that a single linear trend best describes the entire dataset. To address this, a piece wise regression was also performed with two parts. Piecewise regression (Hudson 1966) with two parts assumes that the data are best described by two regression lines with different slopes that meet at an intersection point that is determined by minimizing the error of the fit to the data. Piecewise regression is similar computationally to standard linear regression by minimizing least-square errors of the data to the model fit. However, since the two lines meet at an intersecting point, the curve is not differentiable and thus precludes traditional numerical techniques based on taking derivatives. Instead, since there is a limited number of possible values for the intersection, the Nelder-Mead direct search method (Lagarias et al. 1998) is employed using the ‘fminsearch’ function in Matlab (The Mathworks Inc.) to find the intersection that produces two linear regression lines with the lowest least square errors.

After computing the piecewise regression and the linear regression for each participant, the model fit error terms were compared and the model with the lowest error of the sum of square residuals was selected for each participant. For those participants where piecewise regression was selected, a tuning point was defined as the point of intersection of the two regression curves. The slope of the data before the tuning point was then used for ordering those participants better fit with piecewise regression. Both participants with either type of regression were then ordered for each parameter by magnitude and sign of the parameter.

Chapter 3

RESULTS

Kinematic Parameters

Sample reach data. The velocity profile for a single participant during an exemplary reach in the middle of block 3 and in the middle of block 2 are presented in *Figure 6*. For the normal reach in block 3, the participant had a smooth trajectory with an overall bell shaped velocity curved with some adjustment near the end likely for grasping the cone. For the altered trajectory in block 2, the participant curved their hand to the right as prescribed by the feedback. However, the velocity profile shows many more hesitations, particularly in the deceleration of the movement, which was typical for all subjects.

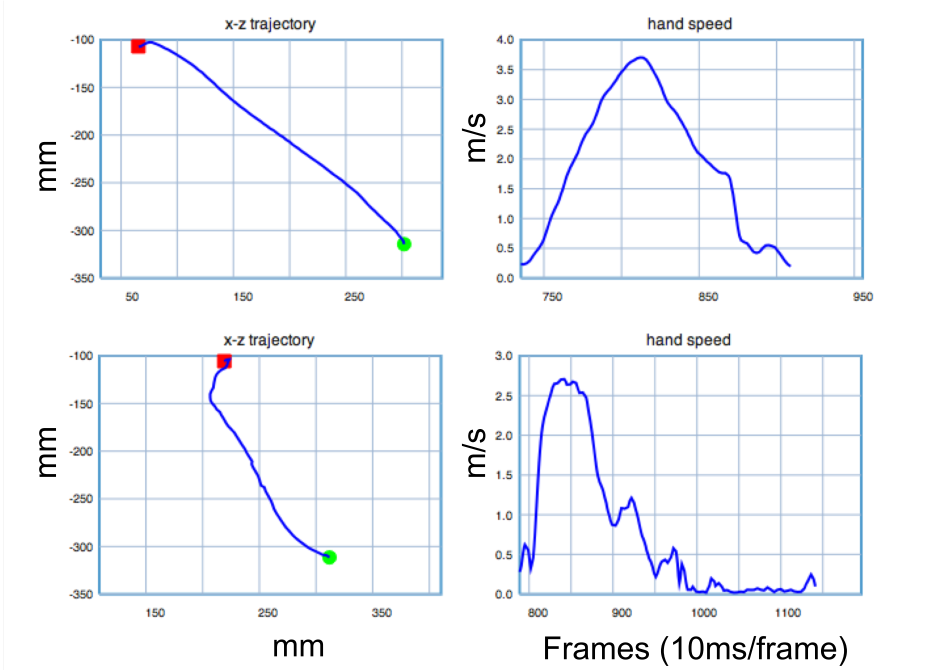

Figure 6. Example reach data in block 2 (bottom figures) and block 3 (upper figures) for a single participant showing the trajectory and the hand speed in the direction towards the cone from the rest position.

Group results. Individual participant kinematic error values per trial are shown in *Figure 7*. It is clear that there are large differences between blocks that had normal reaches compared to those that had the perturbed reaches. Specifically, for the three parameters considered here, the error values were lower in blocks 1 and 3 than in blocks 2 and 4.

Several participants (1, 3, 4, 5, 7) showed typical motor learning patterns of decreasing supination error in block 2. For all participants block 3 and block 1 values and trends were similar. For the number of phases, there is a split between participants (1, 10, 13, 16, 21) who had a large number of phases (between 5 and 10 phases) and participants (2,3,5) with low number of phases (between 1 and 5 phases). Most participants however showed a low number of phases in blocks 1 and 3, which is expected since an unusual reach was not necessary for those blocks. Trajectory errors decreased in block 2 for most participants.

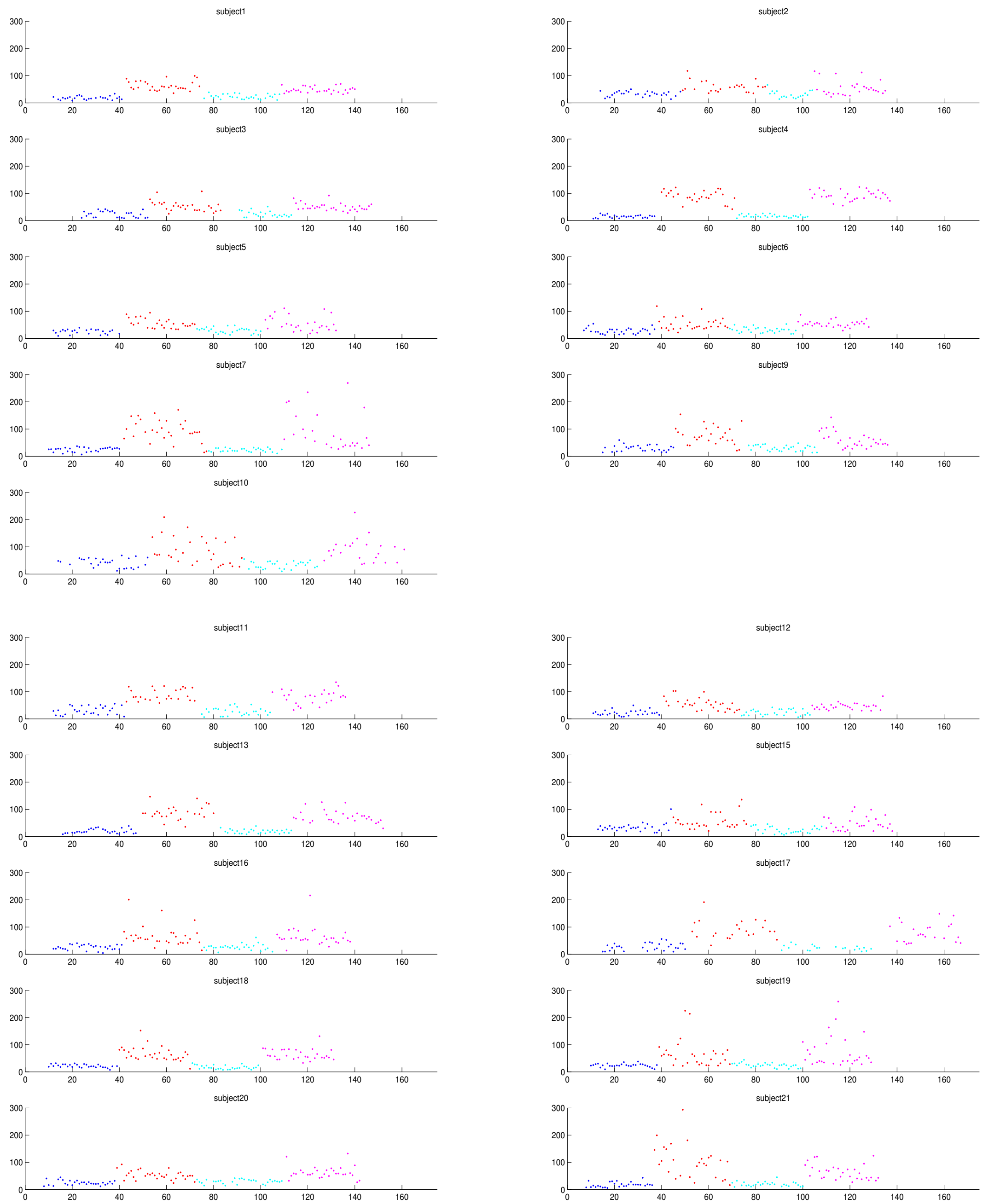

Figure 7. Trajectory error in mm (y-axis) by reach trial (x-axis) for all participants. Each color is a separate block (i.e. blue = 1, red = 2, cyan = 3, magenta = 4).

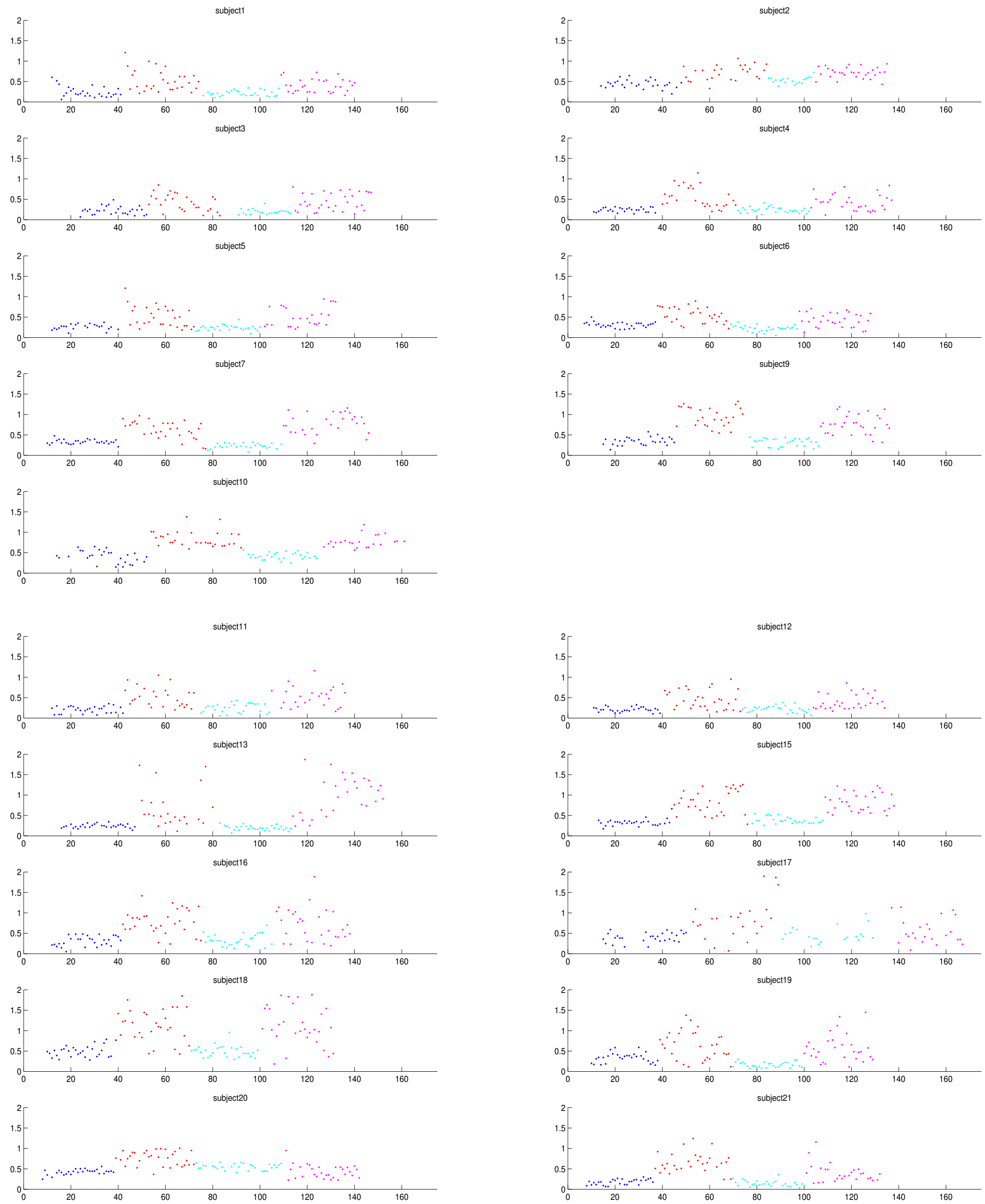

Figure 8. Supination error (y-axis) by reach trial (x-axis) for all participants. Each color is a separate block (i.e. blue = 1, red = 2, cyan = 3, magenta = 4).

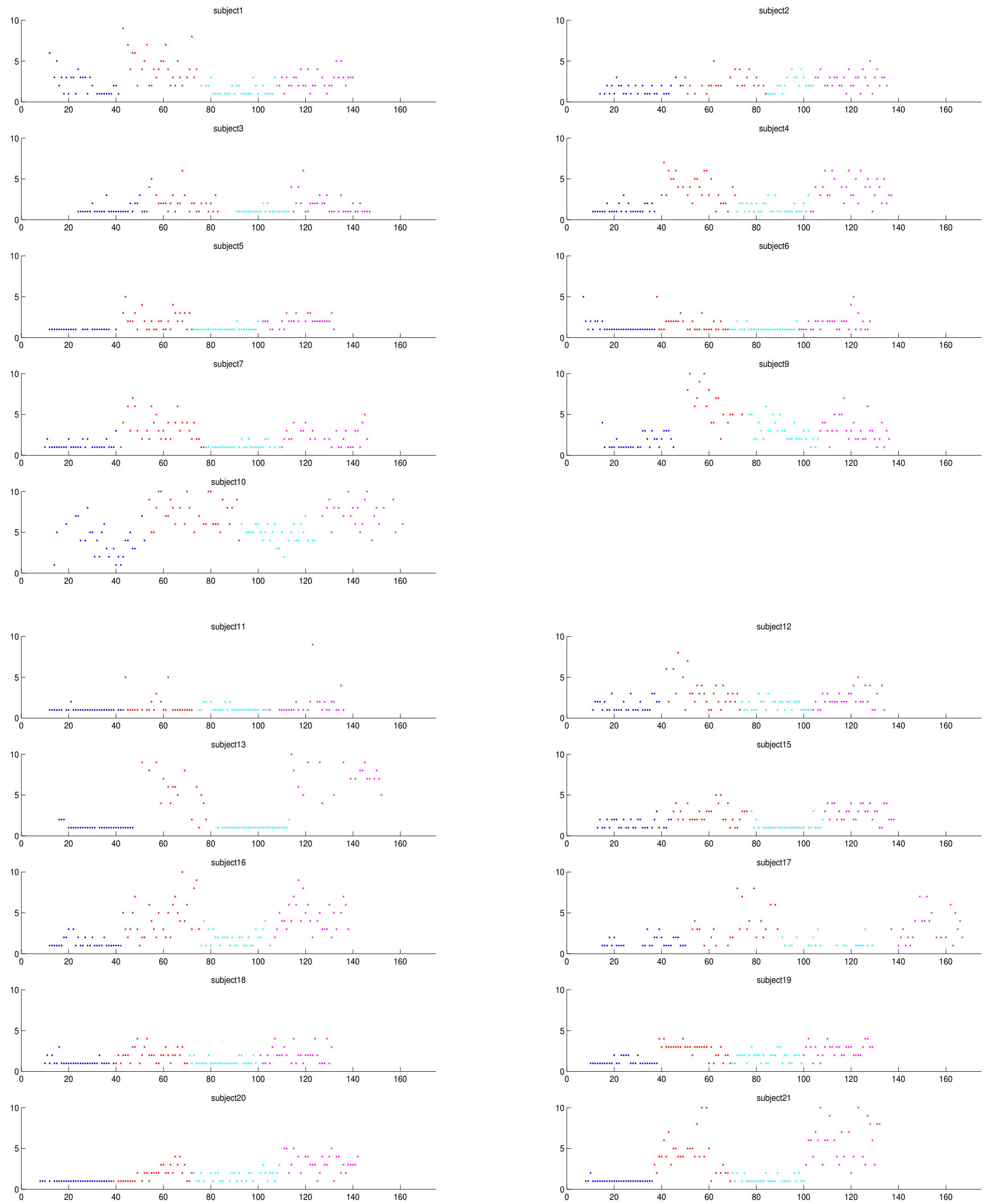

Figure 9. Number of phases in velocity (y-axis) by reach trial (x-axis) for all participants. Each color is a separate block (i.e. blue = 1, red = 2, cyan = 3, magenta = 4).

Initially, changes in the mean values of the kinematic parameters for all subjects were observed to observe group level trends for each kinematic parameter. To do so, the three kinematic parameters for each block were separated into five sub-blocks. For each sub-block, the mean and standard deviation for each kinematic parameter were then computed. The mean and standard deviation as a function of sub-block number are presented in *Figure 10*.

As seen in *Figure 10*, the standard deviations within each window were very large due to the great inter-participant variance. As a result, while some trends such as a decrease in trajectory error and velocity phases in block 2 and relatively constant values for blocks 1 and 3 were observable, a participant specific method of analysis was required.

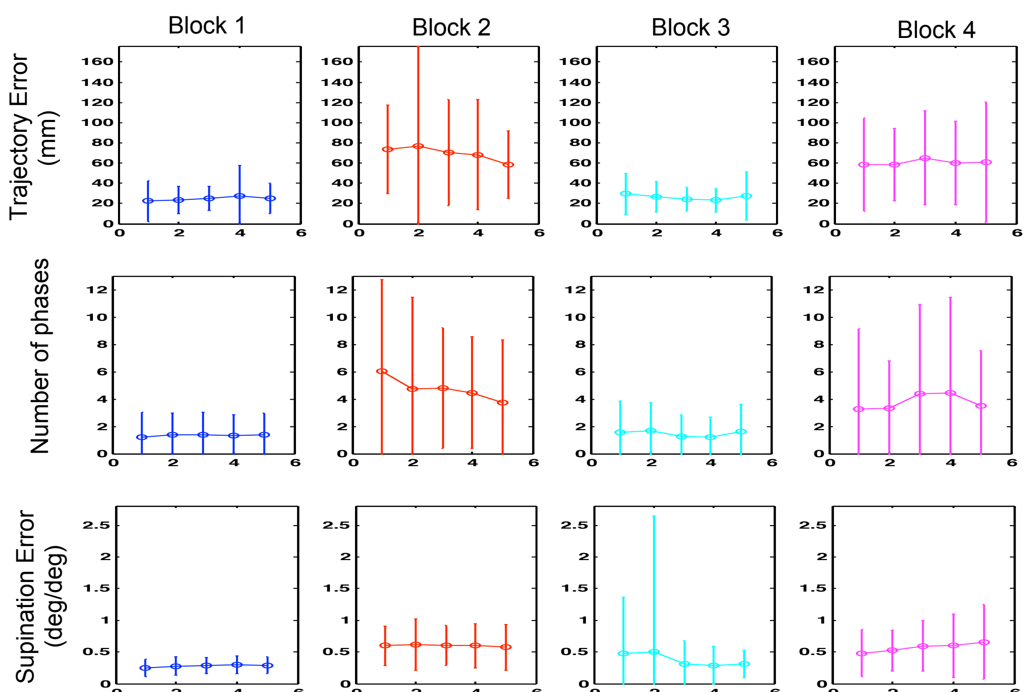

Figure 10. Means and standard deviations of the data divided into five sub blocks for three kinematic parameters.

Regression

Robust regression was used to observe if there were improvements or worsening in the different kinematic parameters. Block 2 was the focus of this modeling since that is where most of the learning is likely to have occurred and thus be the most useful for ordering different participants by the amount of motor learning occurring during the trial. Some participants were better fit with a piecewise regression. In *Figure 11*, the trajectory error for participant 5 in block 2 is shown. Participant five was a better fit with a two-piece regression curve but for illustrative purposes the standard regression curve is also plotted. If a single regression curve were used with participant five, the changes that occurred early in the block would have been lost as shown by the differing slopes of the blue and green curves.

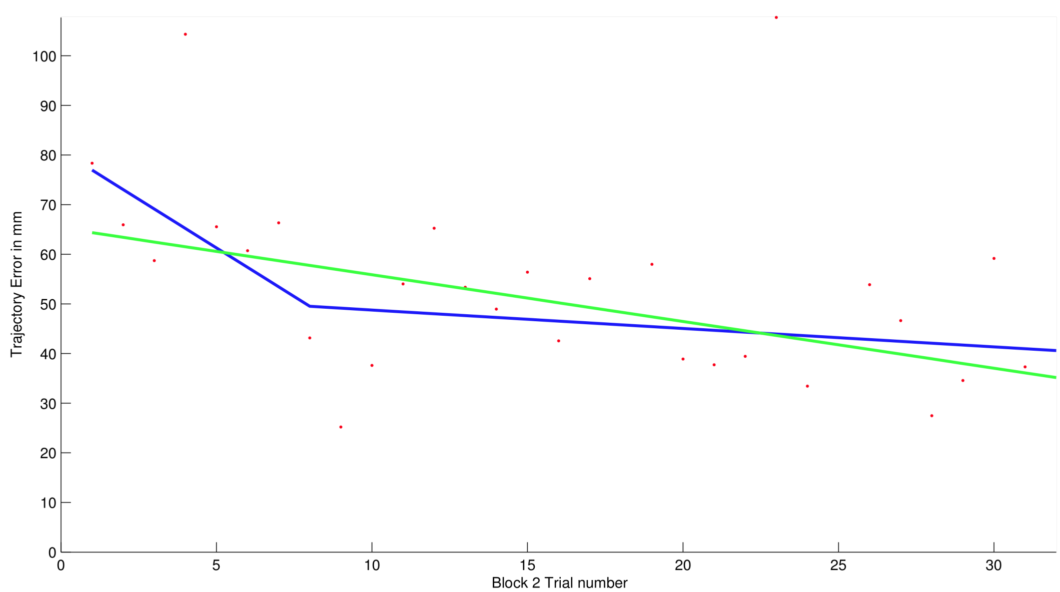

Figure 11. Trajectory error for participant 5 showing different slopes with (blue curve) and without (green curve) piecewise regression

The slopes of the robust regression curves for different parameters are shown in Table 3. For those participants who were better fit with a 2 piece regression, the slopes are included for the points up to the tuning point and are also marked with an asterisk. Each parameter is ordered by the magnitude and sign of the slope. The slope values are normalized by the maximum slope for that parameter so that comparisons can be made across different parameters. The table demonstrates that some participants (17,15,16) showed worsening across multiple parameters while some showed improvement in multiple parameters (participants 1,3,4,12, 21). Interestingly, some participants showed improvement in one parameter with worsening in another (participants 11,20).

Table 3

Participant Ordering for Robust Regression Slopes for Entire Block or up to a Tuning Point, Ordered by the Slope for each Parameter. Parameters have been normalized by the maximum value for the parameter.

Number of Phases		Trajectory Error		Supination Error	
Participant	Slope	Participant	Slope	Participant	Slope
1*	-1.00	6	-1.00	1*	-1.00
9	-0.32	3	-0.27	12	-0.47
13	-0.21	21	-0.18	5	-0.12
12	-0.09	4	-0.18	3	-0.11
4*	-0.09	1*	-0.14	7	-0.10
21	-0.08	10	-0.10	4	-0.10
19	-0.06	7	-0.10	19	-0.10
7	-0.06	12	-0.09	11	-0.08
3*	-0.03	9	-0.07	6	-0.08
10	-0.03	5	-0.07	13	-0.08
6*	-0.02	18	-0.07	18	-0.04
5	-0.02	19	-0.06	10	-0.04
15	-0.01	2	-0.05	9*	-0.03
18	0.00	20	-0.05	20	-0.02
11	0.00	16	-0.04	16	0.01
2*	0.02	15	0.00	21	0.01
17	0.06	17	0.00	2	0.05
20	0.07	11	0.03	15	0.05
16	0.10	13	0.04	17	0.14

Considering a negative slope of the regression curve as an indication of improvement, the total number of parameters that showed improvement (i.e. a negative slope) can be used as a measure of the improvement in multiple parameters. In addition, if the hypothesis that improvements should occur in multiple parameters, the mean can also be used to as a measure of overall improvement. Sorting the rows by the number of means and number of improvements as shown in Table 4 reveals that some participants (17) did not improve in any parameters or only in one (participants 2, 16).

Table 4

Robust Regression Slopes for Different Parameters Sorted by the Number of Improving Parameters. Parameters have been normalized by the maximum value for the parameter.

Participant ID	Number Phases	Trajectory Error	Supination Error	Average improvement	Number of improvements
1	-0.14*	-1.00*	-1.00*	-0.71	3
6	-1.00*	-0.08	-0.02	-0.37	3
12	-0.09	-0.47*	-0.09	-0.22	3
9	-0.07	-0.03	-0.32*	-0.14	3
3	-0.27*	-0.11	-0.03	-0.14	3
4	-0.18*	-0.10	-0.09	-0.12	3
7	-0.10	-0.10	-0.06	-0.09	3
21	-0.18	0.01	-0.08	-0.08	2
13	0.04	-0.08	-0.21	-0.08	3
19	-0.06	-0.10	-0.06	-0.07	3
5	-0.07	-0.12	-0.02	-0.07	3
10	-0.10	-0.04	-0.03	-0.06	3
18	-0.07	-0.04	0.00	-0.04	3
11	0.03	-0.08	0.00	-0.02	2
20	-0.05	-0.02	0.07	0.00	2
2	-0.05*	0.05	0.02	0.01	1
15	0.00	0.05	-0.01	0.01	2
16	-0.04	0.01	0.10	0.02	1
17	0.00	0.14	0.06	0.07	0

The data in **Error! Reference source not found.** are visualized in *Figure 12*. The graph reveals that there were some participants (1,6,9,12) that improved with much larger magnitudes compared to the others. However, not all of those participants that showed the largest magnitudes necessarily improved the same amount in all three parameters. For example, subject six had large improvement in trajectory error with minor gains supination error and number of phases. Similarly, subject twelve improved in supination error with a much greater magnitude than trajectory error or number of phases. Only 7 of 21 subjects showed any worsening and no subjects appear to have large magnitudes of worsening or worsening in all three parameters. Meanwhile participants 1, 3-10, 12, and 19 improved in three parameters. The improvements in multiple parameters are best described by the average of the three parameters (shown in purple in *Figure 12*) as long as the assumption that the three different parameters contribute equally to the mean is acceptable. These results are examples of two methods of characterizing motor learning: 1. ranking subjects by the magnitude of improvement in various parameters and 2. ranking subjects by the number of parameters in which they improved.

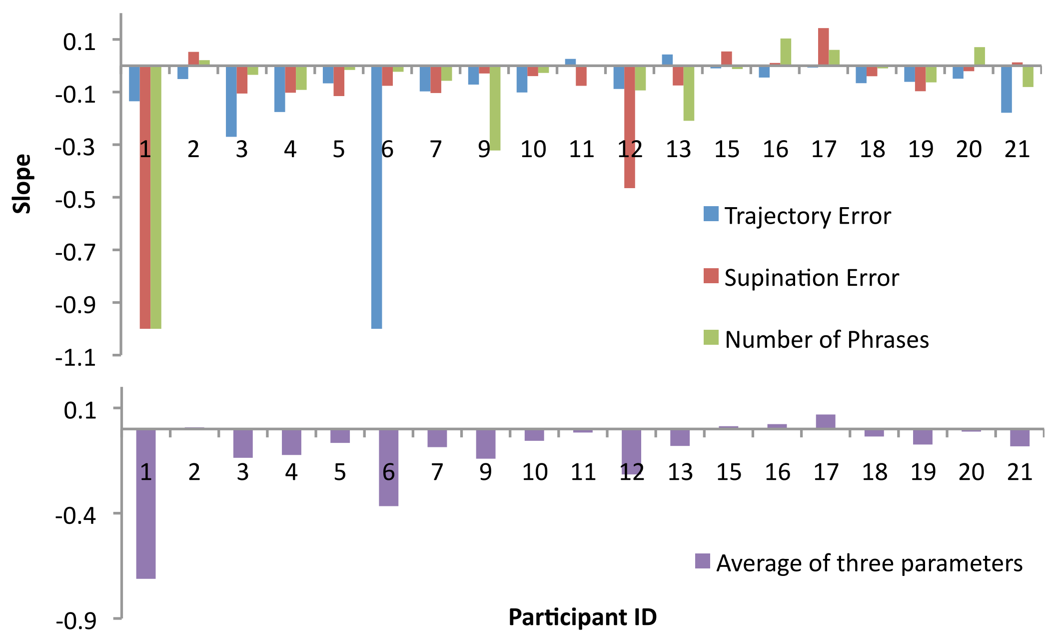

Figure 12. Slopes for various parameters (normalized by the maximum slope value for the parameter) and the average of the three kinematic parameters.

The correlations between different parameters were investigated for each participant and are presented in *Figure 13* and *Figure 14*. The correlation plots reveal how one parameter changes with another. For example, for participant 7, trajectory error and number of phases are highly linked. For participant 16, however, the number of phases has no relationship with the trajectory error. From the correlation plots it can be also observed that for many participants there seems to be a convergence towards a clustering of later reaches (orange/red) with the initial reaches (in blue) further from the clusters.

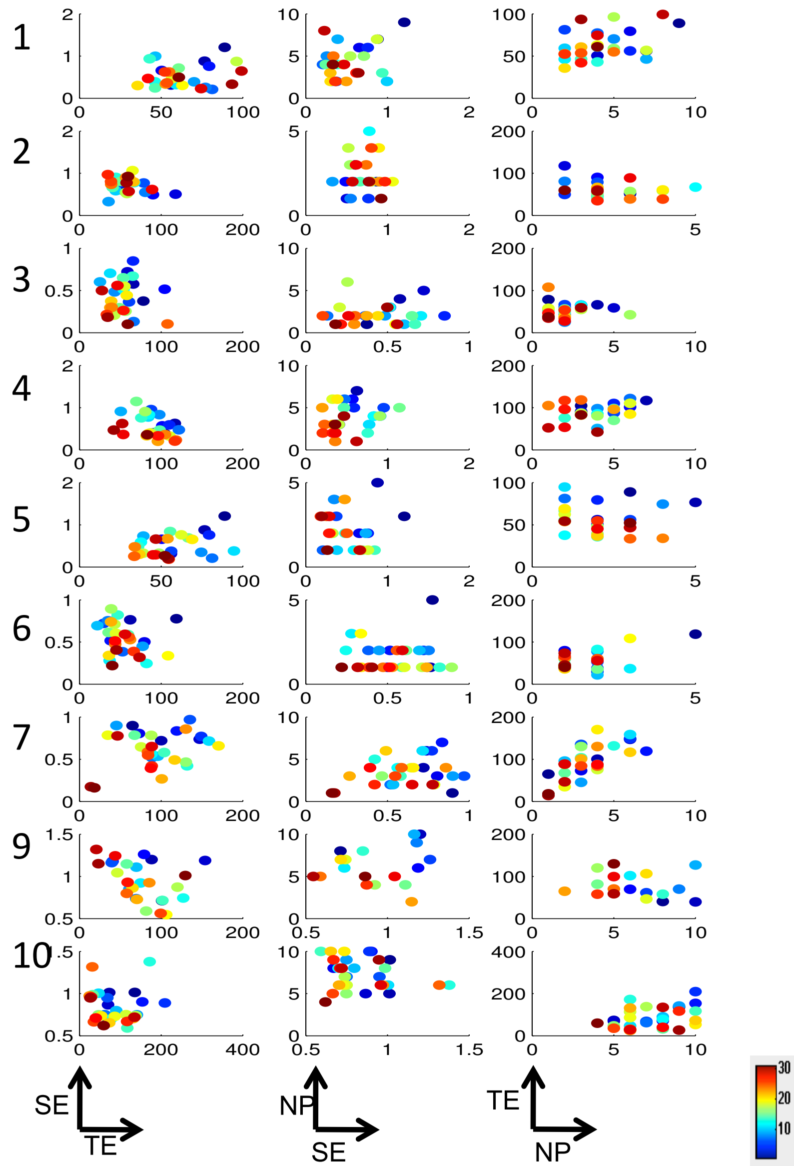

Figure 13. Correlations in block 2 reaches by pairs of kinematic parameters for participants 1-10. Each column of plots is a different pair of comparisons. The value of the kinematic parameter at each reach is plotted against another kinematic parameter. The trial number for the block is represented by the gradient (blue=early reaches, red = later reaches).

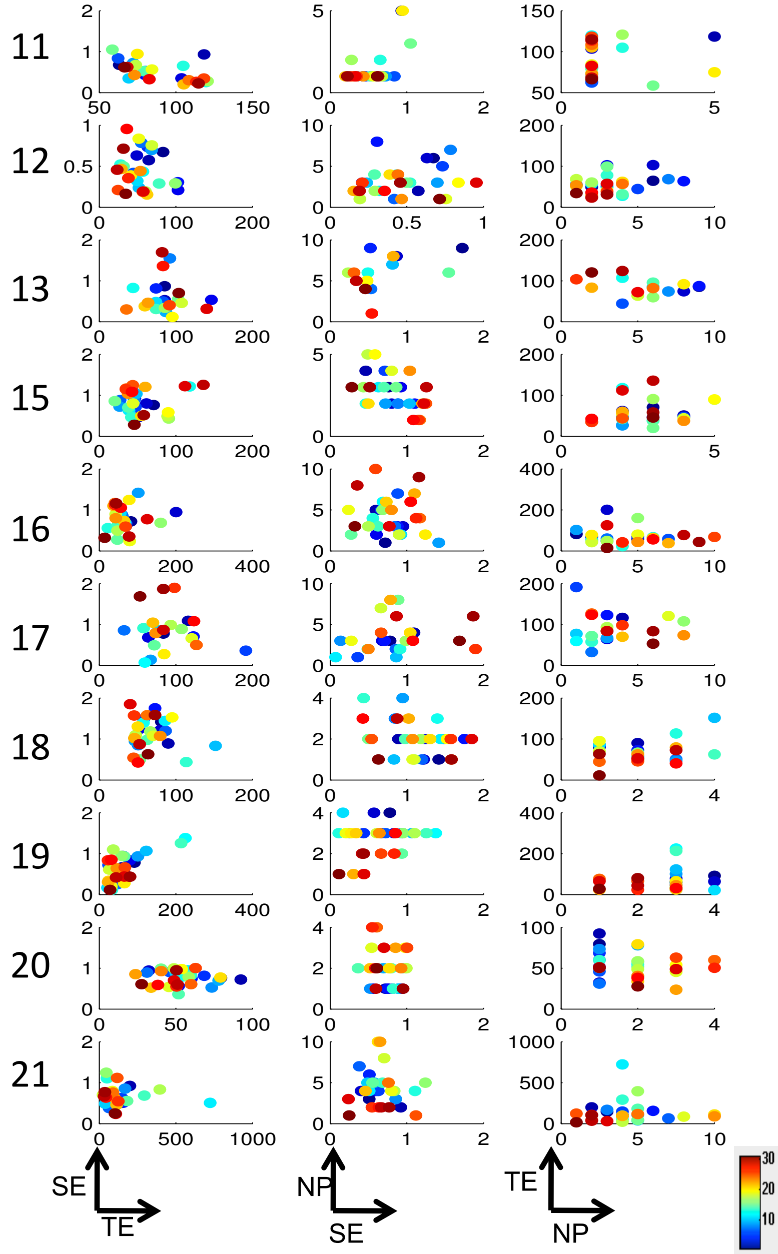

Figure 14. Correlations in block 2 reaches by pairs of kinematic parameters for participants 11-21. Each column of plots is a different pair of comparisons. The value of the kinematic parameter at each reach is plotted against the value of another kinematic parameter. The trial number for the block is represented by the gradient (blue=early reaches, red = later reaches).

Finally, the correlation between participant performances for the entire block was investigated. Number of phases and supination error appear to have a linear relationship. However, trajectory error is inconclusive due to the outlying points. It appears that there are two lines that could fit well, suggesting that trajectory error may have a different mechanism for movement planning than the supination or velocity profile.

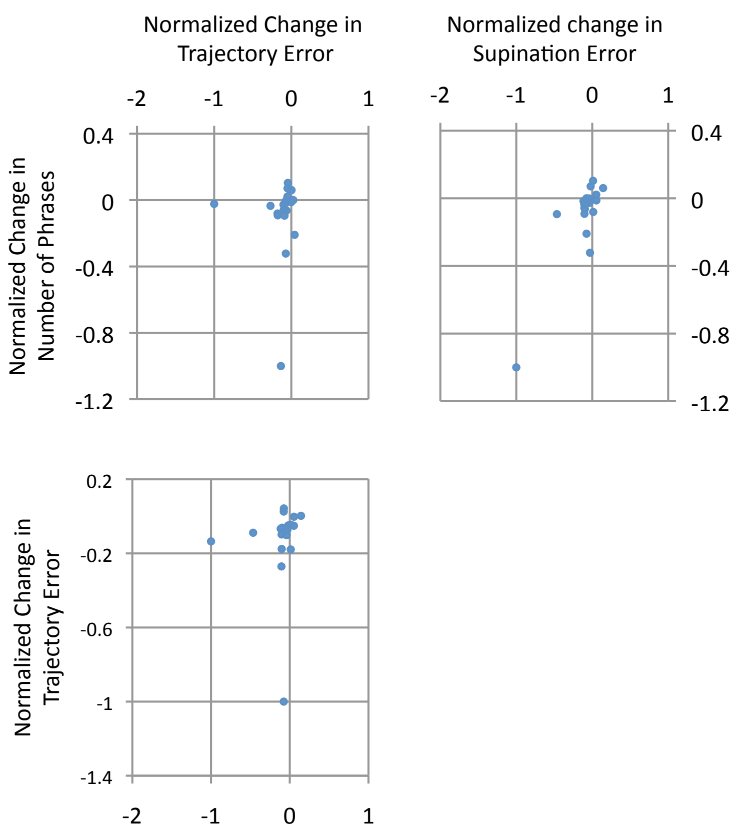

Figure 15. Correlations between pairs of two parameters slope value for block 2 for each participant. (Each point is a participant's slope values in block 2 for the two parameters).

Chapter 4

DISCUSSION

During the motor learning process, it can be expected that various error measures reduce with practice. Ideally, analyses of motor learning are performed on movement data until every participant reaches a steady state value for their errors. This is impractical for applications for real-time monitoring and rehabilitation applications because the amount of time available with participants is restricted. This experiment mimicked these real-world conditions in order to understand the feasibility of using real-time monitoring and simultaneous EEG/EMG recording. To address the previous concerns a dual method for analyzing participants was proposed that takes into account three possible outcomes for the participants'. These outcomes were as follows: One, a participant was able to reach as steady value for their reaches. Two, there were not enough trials for the participant to reach a steady value. Three, the participant was not showing any kind of improvement.

Participants that reached a steady value or had a change in strategy were identified by using the piecewise regression. If the rate of improvement suddenly changed or if they had an initial rapid decrease in error to a plateau, it would be detected by the piecewise regression. For participants who were still continuing to learn, as well as who didn't learn at all could be identified using robust regression to look at the slope of the errors. In addition to those outcomes, the participant's ability to show an integrated improvement (across multiple parameters) was explored using averages of different slope values as well as correlating the performance of specific parameters.

During the experiments, it was observed that some participants were fatigued during the fourth block. However, the block 3 was an indicator of fatigue if they had deterioration in normal reaches in block 3 as compared to block 1. Some participants reported difficulty on fully understanding all of the feedback. In particular, the feedback for the supination/pronation of the forearm was confusing to many participants. However, most participants seemed to understand the curved trajectory that they were required to perform. Some participants that had reported previous experience playing video games appeared more confident in using the system.

There were some limitations to the possible analyses related to the challenges in the study. First, there were a low number of trials per block. This necessitated using simple models to describe the data because there was not enough data to fit more complex curves to the data. In addition, the short duration of blocks resulted in high variability in the data, which precluded group level analysis.

For future studies that require kinematic modeling of participants, using only two blocks with more reaches per block would allow for stronger models to be developed to ensure that the results for all participants stabilized so that error variance is reduced to a minimum. Ideally, the duration of the experiment would be extended to collect more data. However, with the setup time of about one hour for the system and an hour of data collection, fatigue would be a concern for extending the duration of a study.

While only three parameters were studied in this experiment, other kinematic parameters could be computed as well to expand the current framework. With higher numbers of parameters other dimensionality reducing measures such as principal component analysis or factor analysis could be performed to identify underlying principles beneath motor learning.

Finally, while this study focused on block 2, further work could be done comparing block 2 with block 4 to create other methods of categorization. However, in block 4, the responses might be different because the participants are recalling a movement rather then learning it from scratch, so a direct comparison of slopes may not be ideal.

Chapter 5

CONCLUSION

It was possible to engage participants in motor learning, as revealed by improvements in kinematic parameters using the mixed reality rehabilitation system. A combination of robust regression, piecewise regression and correlation were used to characterize participants based on motor learning of three kinematic parameters. The presented methods can be applied to numerous other kinematic parameters to characterize different participants motor learning. Thus, various measures can be used to identify different participants based on their behavior, which can then be used to correlate with EMG/EEG data.

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APPENDIX A

IRB APPROVAL

ARIZONA STATE UNIVERSITY
RESEARCH AND ECONOMIC AFFAIRS

Office of Research Integrity and Assurance

To:	Thanassis Rikakis BKYD
From:	Carol Johnston, Chair Biosci IRB
Date:	11/04/2009
Committee Action:	**Expedited Approval**
Approval Date:	11/04/2009
Review Type:	Expedited F4
IRB Protocol #:	0910004413
Study Title:	EEG Correlates of Reaching and Grasping During Mixed Reality Stroke Rehabilitation
Expiration Date:	11/01/2010

The above-referenced protocol was approved following expedited review by the Institutional Review Board.

It is the Principal Investigator's responsibility to obtain review and continued approval before the expiration date. You may not continue any research activity beyond the expiration date without approval by the Institutional Review Board.

Adverse Reactions: If any untoward incidents or severe reactions should develop as a result of this study, you are required to notify the Biosci IRB immediately. If necessary a member of the IRB will be assigned to look into the matter. If the problem is serious, approval may be withdrawn pending IRB review.

Amendments: If you wish to change any aspect of this study, such as the procedures, the consent forms, or the investigators, please communicate your requested changes to the Biosci IRB. The new procedure is not to be initiated until the IRB approval has been given.

Please retain a copy of this letter with your approved protocol.